# FastMRI: High-Quality Brain MRI Reconstruction

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## Introduction

Compressed Sensing (CS) MRI accelerates imaging by reconstructing high-quality images from undersampled k-space data, crucial for reducing scan times in clinical settings. Generative Adversarial Networks (GANs) provide effective solutions for rapid CS-MRI reconstruction. Our project initially developed DR-CAM-GAN, a U-net-based model with Dilated Residual (DR) networks and Channel Attention Mechanisms (CAM), to reconstruct brain MRIs from the NYU fastMRI dataset at 4× and 8× acceleration. Due to training instability, we transitioned to Wasserstein GAN with Gradient Penalty (WGAN-GP), achieving improved performance with PSNR increasing from 29.1793 dB to 31.1499 dB and SSIM from 0.7834 to 0.8302, enhancing diagnostic potential for brain imaging.

## Methodology

# **Dataset**: NYU fastMRI brain MRI dataset **Training Process**

- DR-CAM-GAN: Trained with standard GAN loss (binary cross-entropy), optimizing a U-net generator with DR networks and CAM for feature enhancement.
- WGAN-GP: Transitioned to Wasserstein loss with gradient penalty to stabilize training at 10× CS acceleration.

#### **Evaluation Metrics**

- Peak Signal-to-Noise Ratio (PSNR): Measures pixel-level accuracy.
- Structural Similarity Index (SSIM): Assesses perceptual quality.

**Implementation**: PyTorch, Adam optimizer, trained on NVIDIA RTX 3090 GPU.

## **Challenges and Advantages**

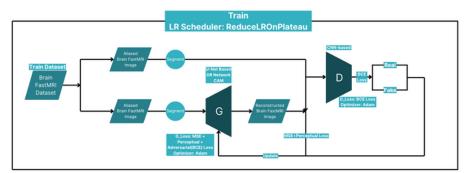
#### DR-CAM-GAN Challenges:

- Mode collapse due to Jensen-Shannon divergence, leading to limited sample diversity.
- Unstable convergence at 8x acceleration, impacting reconstruction quality for complex brain MRIs.

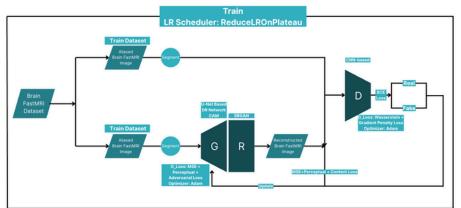
#### WGAN-GP Advantages:

- Wasserstein loss provides smoother gradients, reducing vanishing gradient issues.
- Gradient penalty replaces weight clipping, improving convergence and stability.

## **Architecture (DR-CAM-GAN)**



## **Architecture (WGAN-GP)**



# **Refinement Layer**

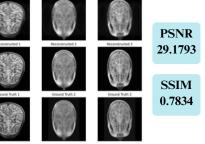
**Purpose**: Enhance reconstructed MRI quality by focusing on anatomical details. **Implementation**: CAM with global max/avg pooling to weigh channel importance, reducing background noise and emphasizing key features.

Ablation Study: CAM reduced background artifacts, improving diagnostic relevance.

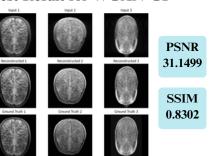
#### **Future Work**

- 1. Adopt StyleGAN2 or Progressive GAN for ultra-high-resolution brain MRI reconstruction
- 2. Apply model to fastMRI knee/prostate datasets for multi-organ applicability.
- 3. Reduce computational cost via mixed-precision training or optimized architectures.
- 4. Develop 3D CS-MRI reconstruction for volumetric brain imaging, aiding surgical planning.

### Test Result for DR-CAM-GAN



## **Test Result for WGAN-GP**



#### Conclusion

The U-net with DR and CAM, paired with WGAN-GP's stable Wasserstein loss and gradient penalty, improved PSNR from 29.1793 dB to 31.1499 dB and SSIM from 0.7834 to 0.8302. These gains highlight WGAN-GP's potential and SRGAN's refinement skill to deliver high-quality, reliable brain MRI reconstructions, paving the way for advanced clinical applications.

#### References

[knoll2020] Knoll et al., Radiol Artif Intell, 2020. doi:10.1148/ryai.2020190007. [li2023] Li et al., Sensors, 2023. doi:10.3390/s23196955. (DR-CAM-GAN [gulrajani2017] Gulrajani et al., NeurIPS, 2017. arXiv:1704.00028. (WGAN-GP [ledig2017] Ledig et al., CVPR, 2017. doi:10.1109/CVPR.2017.19. (SRGAN)